Histograms of Oriented Gradients for Human Detection

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Introduction

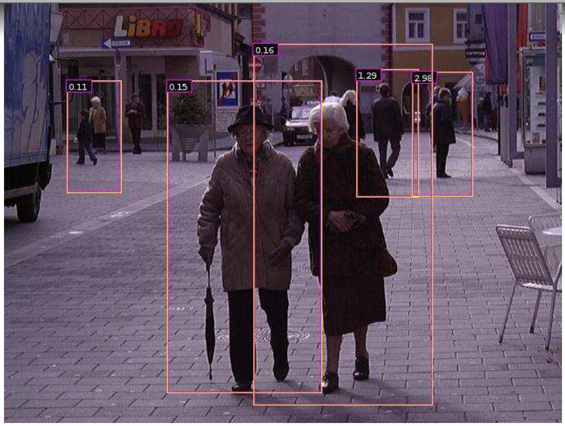
Detect & localize upright people
in static images

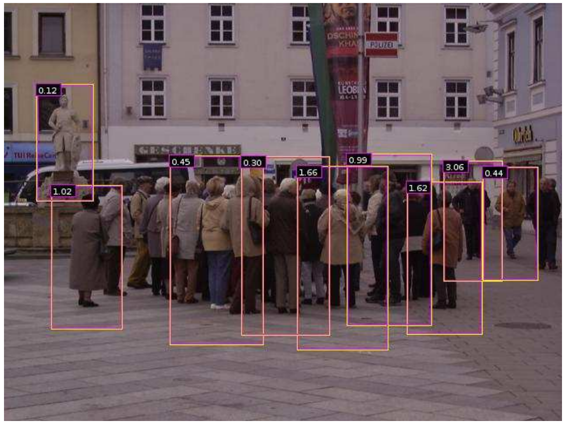
Challenges

- Wide variety of articulated poses
- Variable appearance/clothing
- Complex backgrounds
- Unconstrained illumination
- Occlusions, different scales

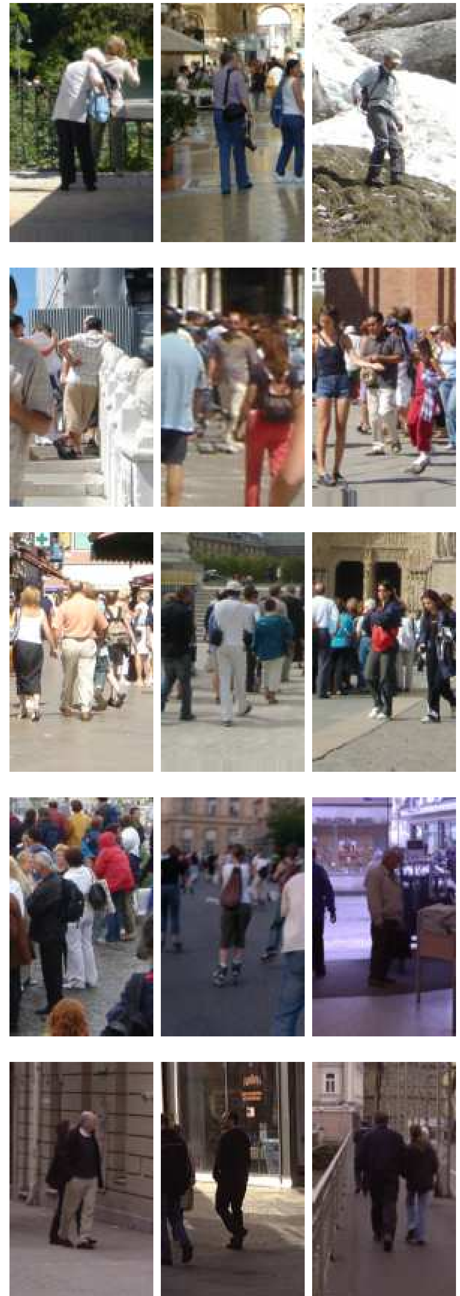
Applications

- Pedestrian detection for smart cars
- Film & media analysis
- Visual surveillance





Approach & Data Set



- We focus on building robust *feature sets*
- Classifier is just linear SVM on normalized image windows, is reliable & fast
- Moving window based detector with non-maximum suppression over scale-space

Data set available
http://pascal.inrialpes.fr/data/human/

Data Set

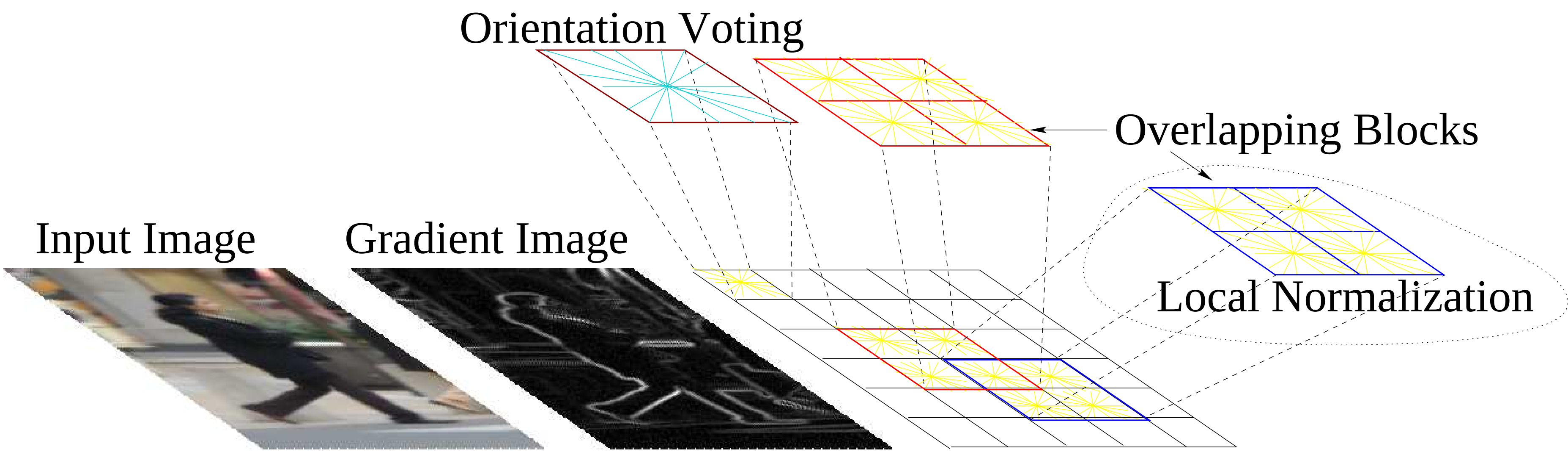
Train	*Test*
614 positive images	288 positive images
1218 negative images	453 negative images
1208 positive windows	566 positive windows
Overall 1774 human annotations + reflections	

Feature Sets

- Haar Wavelets + SVM: Papageorgiou & Poggio (2000), Mohan et al (2001), DePoortere et al (2002)
- Rectangular differential features + adaBoost: Viola & Jones (2001)
- Parts based binary orientation position histograms + adaBoost: Mikolajczyk et al (2004)
- Edge templates + nearest neighbor: Gavrila & Philomen (1999)
- Dynamic programming: Felzenszwalb & Huttenlocher (2000), Ioffe & Forsyth (1999)

- **Orientation histograms**: c.f. Freeman et al (1996), Lowe (1999)
- Other descriptors:
  - Shape contexts: Belongie et al (2002)
  - PCA-SIFT: Ke and Sukthankar (2004)

Processing Chain



Input image → **Normalize gamma & colour** → **Compute gradients** → **Weighted vote into spatial & orientation cells** → **Contrast normalize over overlapping spatial blocks** → **Collect HOG's over detection window** → **Linear SVM** → **Person / non−person classification**

HOG Descriptors

Parameters

- Gradient scale
- Orientation bins
- Percentage of block overlap

Schemes

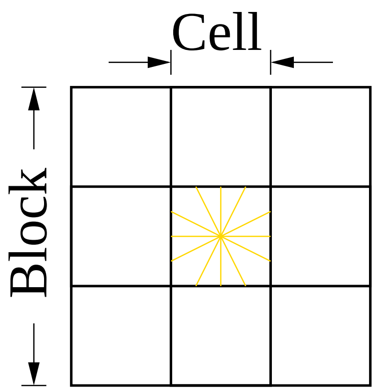
- RGB or Lab, color/gray-space
- Block normalization,

  $L2$-norm, $\mathbf{v} \to \mathbf{v}/\sqrt{\|\mathbf{v}\|_2^2 + \epsilon^2}$

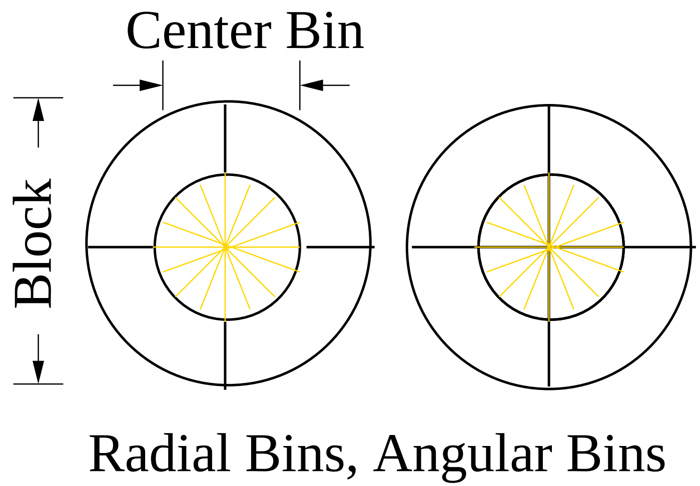
  or

  $L1$-norm, $\mathbf{v} \to \sqrt{\mathbf{v}/(\|\mathbf{v}\|_1 + \epsilon)}$

R-HOG/SIFT

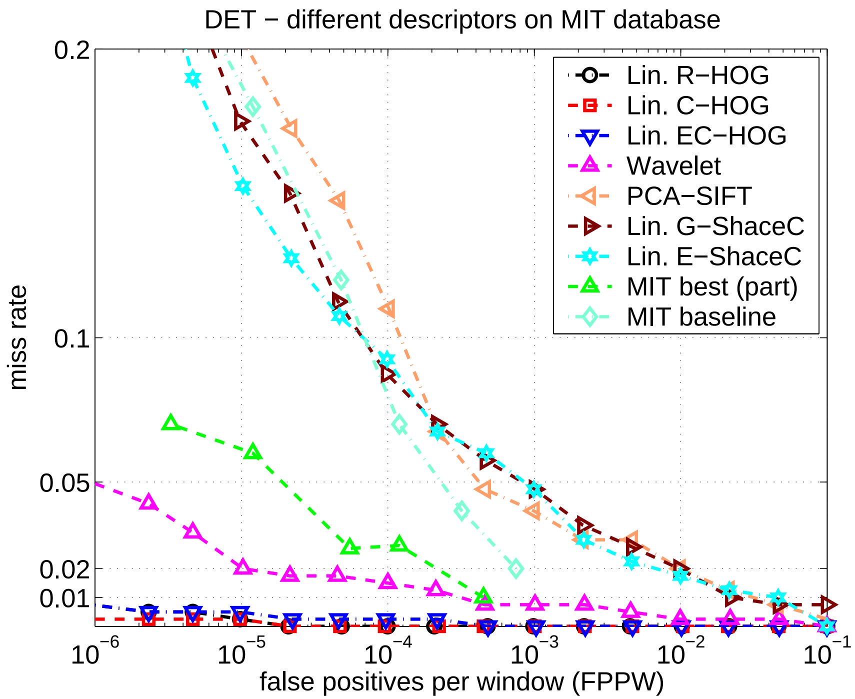


C-HOG

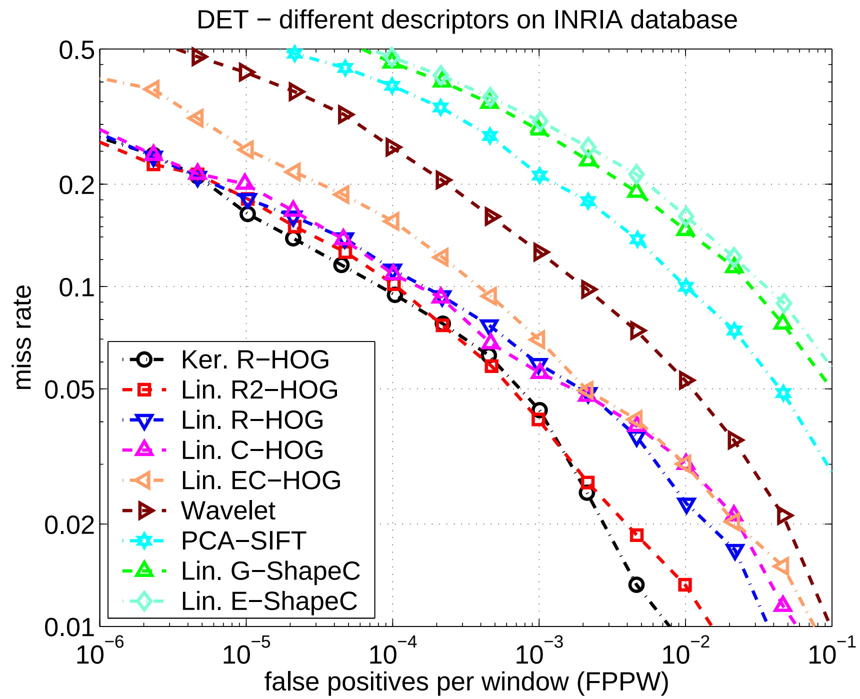


Performance

MIT pedestrian database



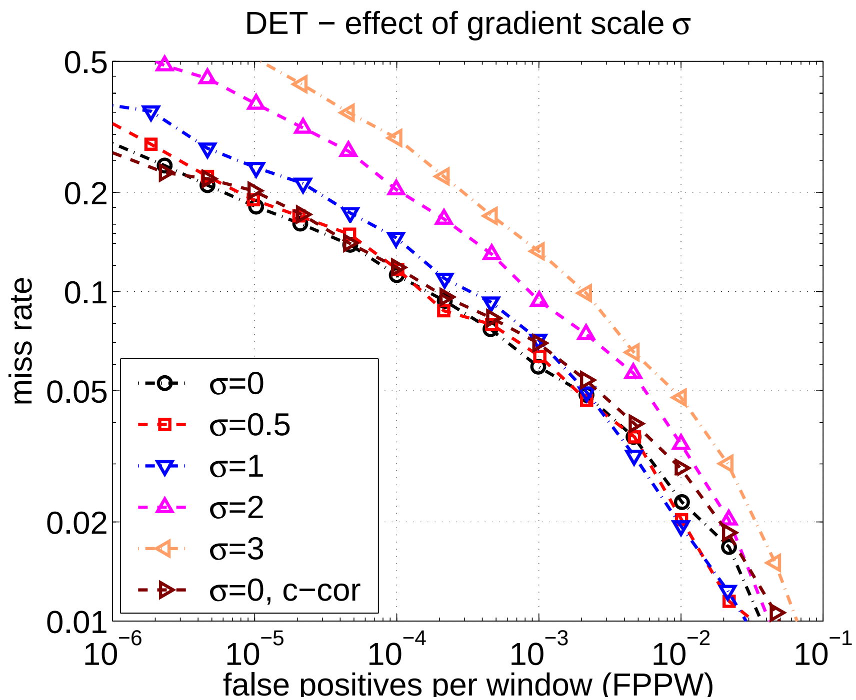
INRIA person database



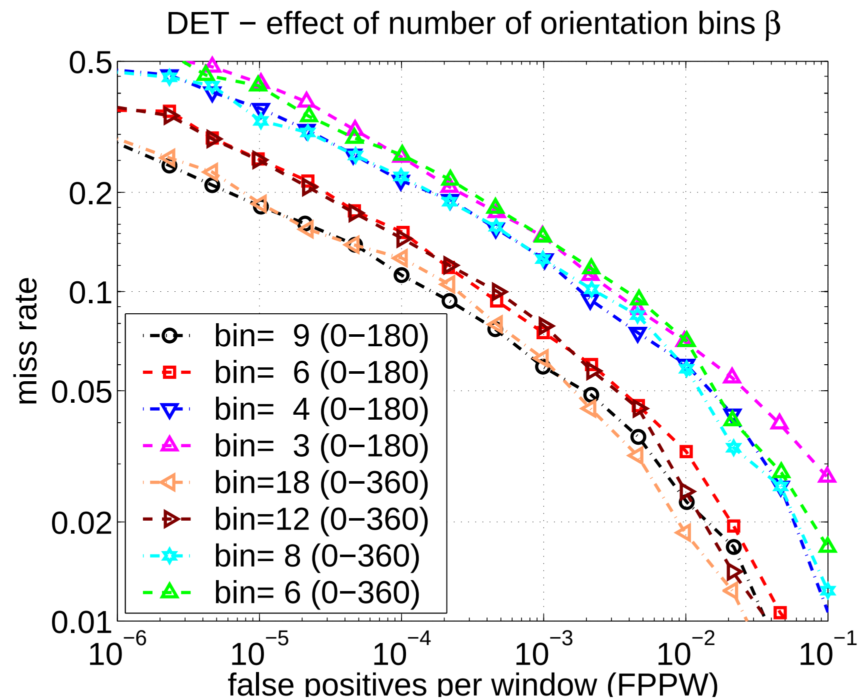
- R/C-HOG give near perfect seperation on MIT database
- Have 1-2 orders of magnitude lower false positives than other descriptors

Gradient Smoothening & Orientation Bins

Gradient scale, σ



Orientation bins, β

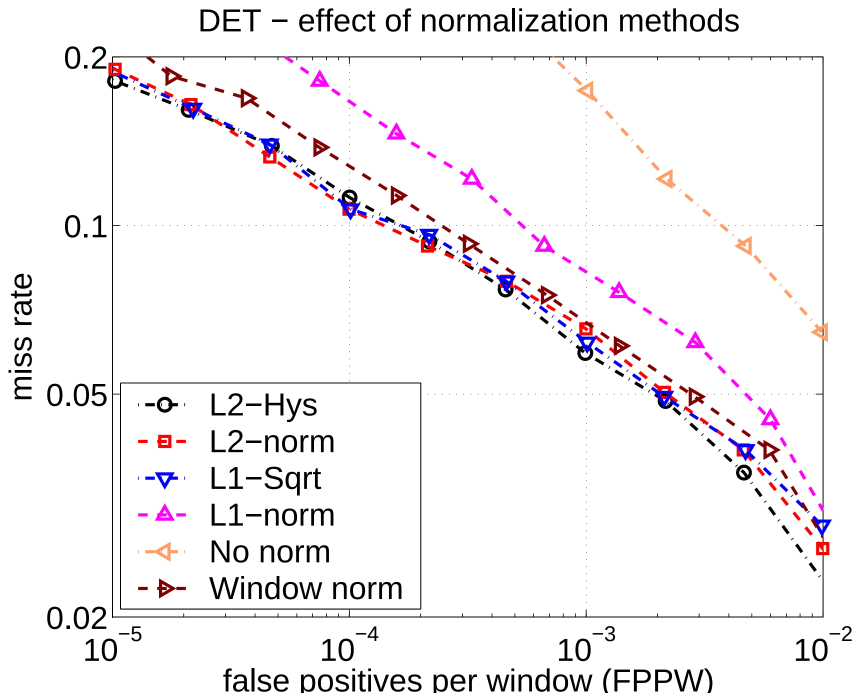


Using simple smoothed gradients & many orientations helps!

- Reducing gradient scale from 3 to 0 decreases false positives by 10 times
- Increasing orientation bins from 4 to 9 decreases false positives by 10 times

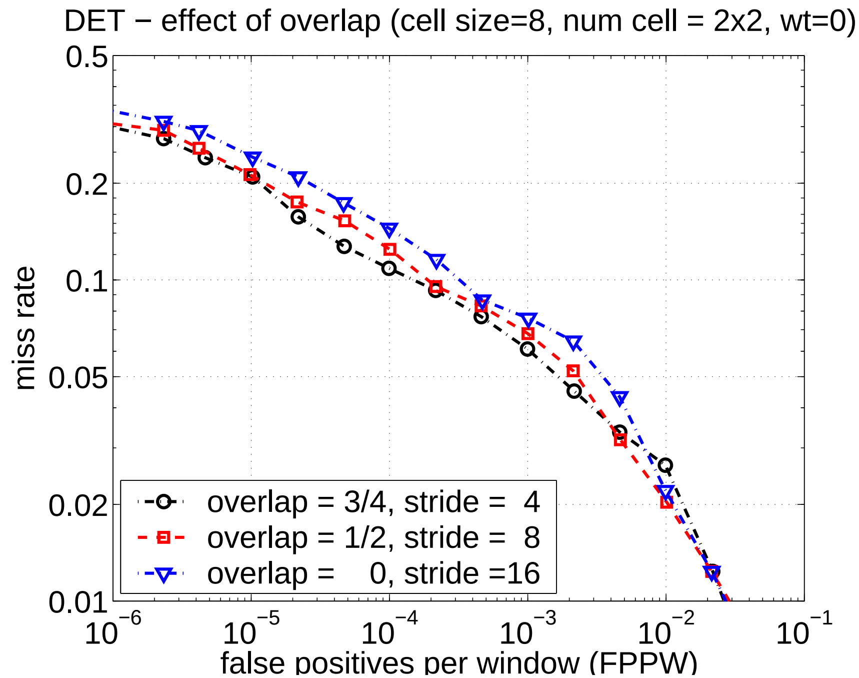
Normalization Method & Block Overlap

Normalization method



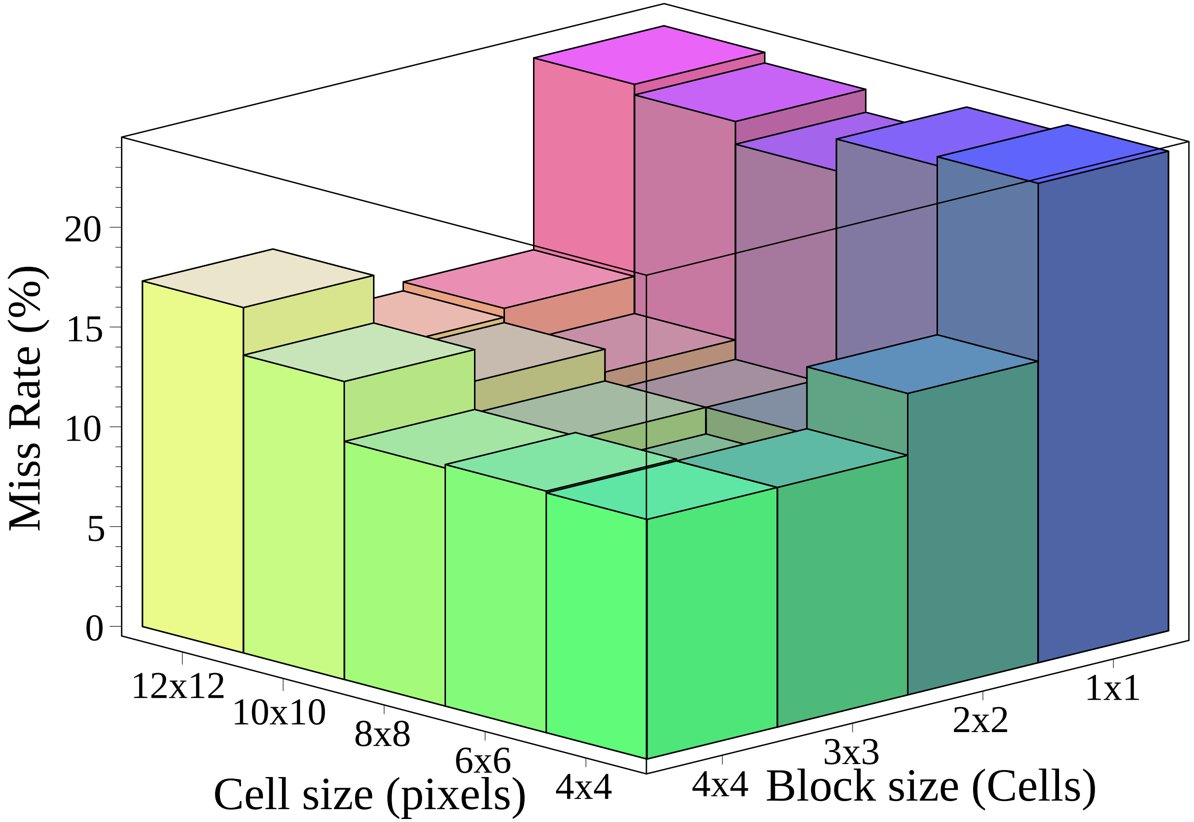
Strong local normalization is essential

Block overlap



Overlapping blocks improves performance, but descriptor size increases

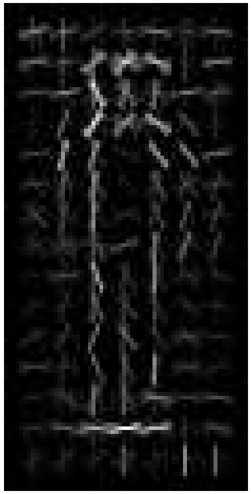
Effect of Block & Cell Size



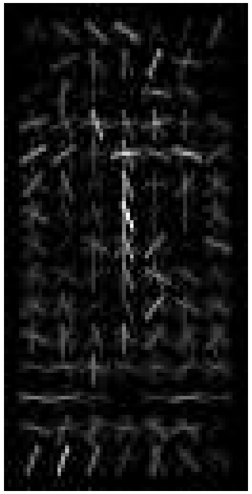
Trade off between need for local spatial invariance
and need for finer spatial resolution

Descriptor Cues

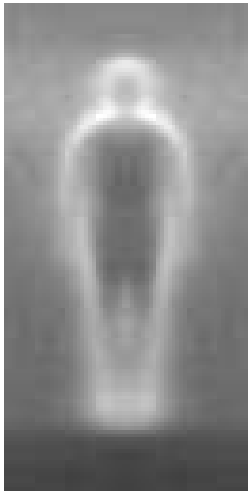
input image



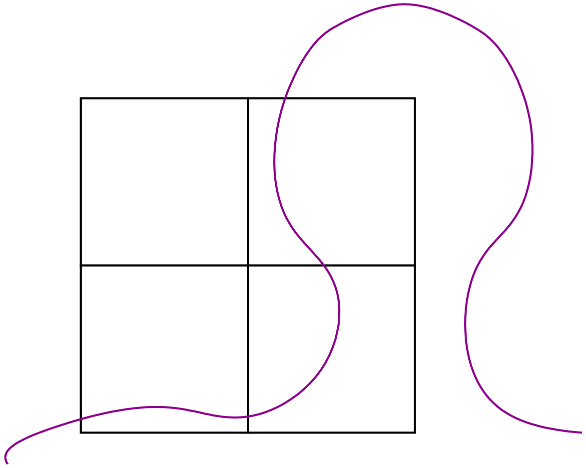
weighted
pos wts



weighted
neg wts



avg. grad



outside in block

- The most important cues are head, shoulder, leg silhouettes
- Vertical gradients inside the person count as negative
- Overlapping blocks those just outside the contour are the most important

Conclusions

Fine grained features improve performance

- No gradient smoothning, $[-1, 0, 1]$ derivative mask
- Use gradient magnitude (no thresholding)
- Orientation voting into fine bins
- Spatial voting into coarser bins
- Strong local normalization
- Overlapping normalization blocks

- A general object classifier
- Also works well for other classes
- Linear SVM is reliable & fast, but not optimal
- Human detection: 90% at 10^{-4} false positives per window

Demo

No temporal smoothning